SIMULATING AIRLINE MARKETING STRATEGIES USING SYSTEM DYNAMICS MODELLING

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ABSTRACT

Marketing airline products and services has always been highly competitive and requires that rigorous strategic planning is put in place for achieving maximum growth and profitability. Customer relationship management which is one of the factors that has direct impact on the overall performance of an airline must be guided and maintained by changing organisational internal and external marketing plans. However, it is very dangerous to find solutions to problems that involve customers and strategic planning by experimenting with real subjects. Therefore, simulation studies have become one of the ways of proffering solutions to such problems. In this paper we present a hypothetical proof-of-principle study that was conducted to demonstrate the feasibility and applicability of using System Dynamics (SD) simulation for studying airline marketing strategies. In conclusion we can say that SD simulation has shown strong potential as a decision support tool in this instance, and we are confident that our prototype can be used as a basis for investigating real-world cases.

INTRODUCTION

Marketing is a core business component in the aviation industry, where the environment is highly competitive and profit margins are often low. Strategic decision-making in airline marketing is a process of high complexity, as it demands effective and careful planning. Furthermore, selling products and services in today's airlines, as it is in other market places, require a specialised skill set and attention to industry needs. Rankin (2009) pointed out that marketing planning in an airport as with other organisations is all about selecting appropriate target groups and formulating a marketing mix to achieve marketing objectives and financial targets. The factors which need to be considered in the dynamic and ever changing airport industry means that airport marketing planning is more than just applying general theory to practice.

Airports are complex socio-technical systems facing constant pressure to improve (among other things) products, facilities, methods, revenue, and general organisation performance. These complexities can be resolved by conducting simulation studies, which have become the predominant way of solving real-world problems where Operations Research (OR) analytical approaches do not succeed.

Researchers working in the field of airport operations have developed many models and tools, using both, analytical and simulation approaches (Manataki and Zografos 2010). But not all areas of airport operations challenges have yet been completely resolved. Faboya and Siebers (2014) recently developed an airport model classification. They adopted Greasley's worldview framework (Greasley 2013) which provides a view into the kind of insight each of the available simulation modelling paradigms (System Dynamics (SD); Discrete Event (DE); Agent Based (AB)) provides. The airport model classification exercise also revealed some areas of airport operations where there is a lack of appropriate decision support tools. One of the gaps identified was the lack of airline marketing strategy models. The goal of this paper is to investigate the feasibility of using SD simulation modelling for studying airline marketing strategies.

LITERATURE REVIEW

Simulation Methods

Modelling various operations in airport have attracted substantial research interest, and quite a number of models and tools proffering solutions to airport operations have been developed with the objective of supporting decision making. Besides analytical methods, which are often used in airport operations management, several simulation modelling methods exists that can be used for this purpose. The main methods used in this context are SD, DE, and AB simulation modeling. SD simulation modelling is a process-oriented, continuous, deterministic simulation modelling approach where processes are modelled at a very high level of abstraction and entities are aggregated (i.e. they lose individual properties, histories, and dynamics). Real-world processes are represented in terms of stocks, flows between these stocks, and information that determines the values of these flows (Forrester 1997). SD simulation modelling is an offspring of the SD methodology which focusses on understanding the behaviour of complex systems over time by dealing with internal feedback loops and time

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delays that affect the behaviour of the entire system (Sterman 2001). It is a very powerful methodology and simulation modeling technology for framing, understanding, and discussing complex issues and problems. DE simulation modelling is a process-oriented, discrete, stochastic modelling approach where the operation of a system is modelled as a discrete sequence of events in time. Each event occurs at a particular instant in time and marks a change of state in the system (Robinson 2004). Finally, AB simulation modelling is an object-oriented, discrete, stochastic modelling approach where a system is modelled as a collection of autonomous decision-making entities called agents. Each agent individually assesses its situation and makes decisions on the basis of a set of rules (Bonabeau 2002). While the individual agents interact with each other and their environment, they produce complex collective behaviour patterns at system level. In this paper we focus on SD modelling and simulation, and the reasons are given next.

Among the scholars that used SD models in the past to address air transport management problems are Manataki and Zografos (2009, 2010), Odoni (1991), and Tosic (1992). Their work focused on the management of airport terminals. Miller and Clarke (2007) used SD models to evaluate strategies for investment in aviation infrastructure and Suryani et al. (2010) used them for simulating different scenarios for expanding passenger terminal capacity.

Simulation models related to airport and airline marketing are very rare. One study we found that is remotely related is that of Minato and Morimoto (2011), which focuses on analysing regional airports as ecosystems. SD simulation modeling is used to propose optimal strategy for sustaining these ecosystems. The study concluded that ticket subsidies combined with measures to enhance non-aeronautical revenue are needed for viability of these regional airports. Another study loosely related to the topic is that of Kuhn et al. (2010), who present an AB model to assist in market share analysis. The model is supposed to help investment analysts to develop earnings forecast for the year ahead. For the case of airport and airline marketing, however, the application of AB simulation modelling to investigate macro level factors, such as those presented by the market share analysis may not give appropriate results. The model needs to be able to consider several feedback loops that result from the structural organisation of the system. Following Greasley's framework (Greasley 2013), these kinds of studies would benefit from using an aggregate modelling approach. For this reason we have decided to use SD simulation modelling for studying marketing behaviour in airline industry.

METHODOLOGY

For approaching the simulation modelling task we first used a tool often used in the "Systems Thinking" community, namely Causal Loop Diagrams (CLD). This is a qualitative modelling approach and helps with the conceptual modelling of the system. The CLD can then be translated into a SD simulation model, which is a quantitative modelling approach that allows studying the dynamics of the system over time. We use some graphical notation for the SD simulation modelling and the software we use for the implementation will then translate the model into a set of ordinary differential equations which, when the simulation is executed, will be solved repeatedly while considering time progression.

CASE STUDY DESCRIPTION

In this section we take a closer look at the airline marketing strategy through a hypothetical proof-of-principle simulation case study. The description of the problem is given below.

Problem Description

A small airline company is faced with low patronage challenges. As a result, the management decided to embark on developing a medium-term strategy to improve the performance of the airline over a period of time, but there are other competitors' airlines around in the same airport competing for the same set of passengers. The total number of people living in the area is considered as the target population of the airlines. Due to limited service counter availability in the terminal, the airline in question currently only uses three service counters to serve their customers.

Airline performance is measured by the revenue and profits the organisation makes over a given period of time, and this depends largely on the number of passengers that the airline can win and retain during this period. Passengers can be won by attractive fares, ranges of services, opening new routes and overall good customer experience. On the other hand, passengers can be lost due to the activities of competitors, poor service quality that may resulted into delay and cancellation of flight, and overall bad customer experience.

Conceptual Model

For defining our conceptual model we have employed Albin’s conceptual modelling framework for SD (Albin 1997). The specific objectives of our hypothetical case study are "to increase airline performance by wining and retaining at least 70% of the total population living in a given area as passengers for a period of 5 years, and to determine the optimum ticket-life-time policy and number of services that wins". Our constraint is that the available number of counters is limited to three. Our assumptions are that members of staff never fail, and that they never go on breaks (they work in shifts). Our simplification is that staff members work 24 hours a day.

MODEL DESIGN

A causal loop diagram provides a way for expressing our understanding of the dynamic, interconnected nature of our world. Such diagrams are constructed by linking together key variables and indicating the causal relationships between them, often ending up in feedback loops. By stringing together several loops, we can create a coherent story about a particular problem or issue (Kim 1992).

The initial CLD in Figure 1 summarises the story of our hypothetical case study. "+" signs are interpreted as "*if* the cause increases, *then* the effect increases (above what it would otherwise have been)" while "-" signs are interpreted as "*if* the cause increases, *then* the effect decreases (above what it would otherwise have been)". "R" refers to a reinforcing feedback loop (feedback loop that reinforces change with even more change) while "B" refers to a balancing feedback loop (feedback loop that seeks a goal).

The diagram presented in Figure 1 consists of three main variables, each expressing a "number of people" in a specific state and of a number of causal loops which influence their states. The variables are: Potential Passengers" (PPs), which are people who might buy a ticket (the base population), "Actual Passengers" (APs), which are people who bought a ticket, and "Dissatisfied Passengers" (DPs), which are people who bought a ticket and are dissatisfied with the current service standard. After a certain delay (which represents the period between purchase and usage of the return ticket) APs and DPs become PPs again. Once they are back in PP state they have forgotten everything that happened to them in the past. In the following we describe the causal loops in form of if-then statements. *If* the number of PPs increases *then* "adoption from promotion" increases. *If* "adoption from promotion" increases *then* the number of APs increases (low fares etc. strengthen the current effect). *If* the number of PPs increases *then* "adoption from recommendation" decreases (recommendation depends on the number of adopters; more potential adopters means less adopters to provide recommendation). *If* "adoption from recommendation" decreases *then* the number of APs decreases (adoption fraction etc. strengthen current effect). *If* number of APs decreases *then* "adoption from recommendation" decreases (less APs means less people provide recommendations to convince PPs to buy a ticket). *If* the number of APs increases *then* - with a delay - the number of PPs increases (once APs have used their return ticket they become PPs again). *If* number of APs increases *then* "service quality" decreases (staff cannot cope with increase in passenger numbers). *If* "service quality" decreases *then* the gap increases. The gap defines the difference between desired and actual service quality (gap = desired service quality – actual service quality). *If* the gap increases (expectations are not reached) *then* - with a delay (a reputation does not change instantly) - "adoption from service reputation" decreases. *If* "adoption from service reputation" decreases *then* the number of DPs increases. *If* the number of DPs increases *then* - after a certain delay - the number of PPs increases (once DPs have used their return ticket they become PPs again).

There are four feedback loops in our diagram. Two of these are reinforcing (leading to exponential growth) and two of these are balancing (leading to goal seeking behaviour). Combined with the fact that we have some delays we would expect some kind of oscillating pattern of behaviour for this kind of system structure (Kirkwood 1998).

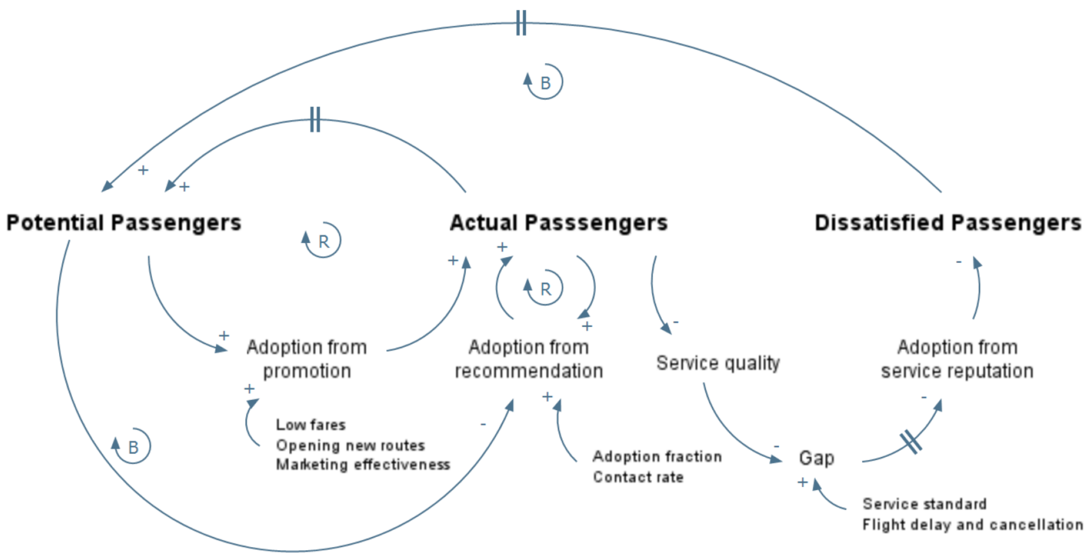


Figure 1: Initial CLD for hypothetical case study

MODEL IMPLEMENTATION

The model described above has been implemented in form of a Stock and Flow Diagram (SFD) in AnyLogic 7.0 (University Edition). AnyLogic is a multi-paradigm Eclipse-based commercial drag and drop modelling and simulation IDE. It can be programmed and extended using Java. A SFD shows relationships among variables which have the potential to change over time (like causal loop diagrams) but distinguishes between different types of variables. Main elements are stocks, flows, information, auxiliaries, and parameters. A stock (depicted as a box) represents an accumulation of "something" over time. A flow (depicted as a valve on a thick arrow) represents a flow or movement of the "something" from one stock to another. Information (depicted as a curved thin arrow) is placed between a stock and a flow and indicates that information about a stock influences a flow. An auxiliary (depicted as a circle) arise when the formulation of a stock's influence on a flow involves one or more intermediate calculations. Parameters (depicted as circles with a triangle) are constants that are set during the initialisation of the model. Figure 2 shows the SD model for the hypothetical system during execution. It includes three stocks and four flows. Located at the bottom are two time series windows displaying stock level changes over time as well as rate changes over time. A copy of the model is available from the authors upon request.

The dynamics of the system are defined as follows. At the initial stage, the stock PPs comprises the total population of the area. The other stocks are empty. Changes in the stocks over time can be expressed through the following equations:

d(PPs) / dt = -PassengerWonRate + ActualPassengerTicketUsageDelay + DissatisfiedPassengerTicketUsageDelay

d(APs) / dt = PassengerWonRate – PassengerLossRate - ActualPassengerTicketUsageDelay

d(DPs) / dt = PassengerLossRate - DissatisfiedPassengerTicketUsageDelay

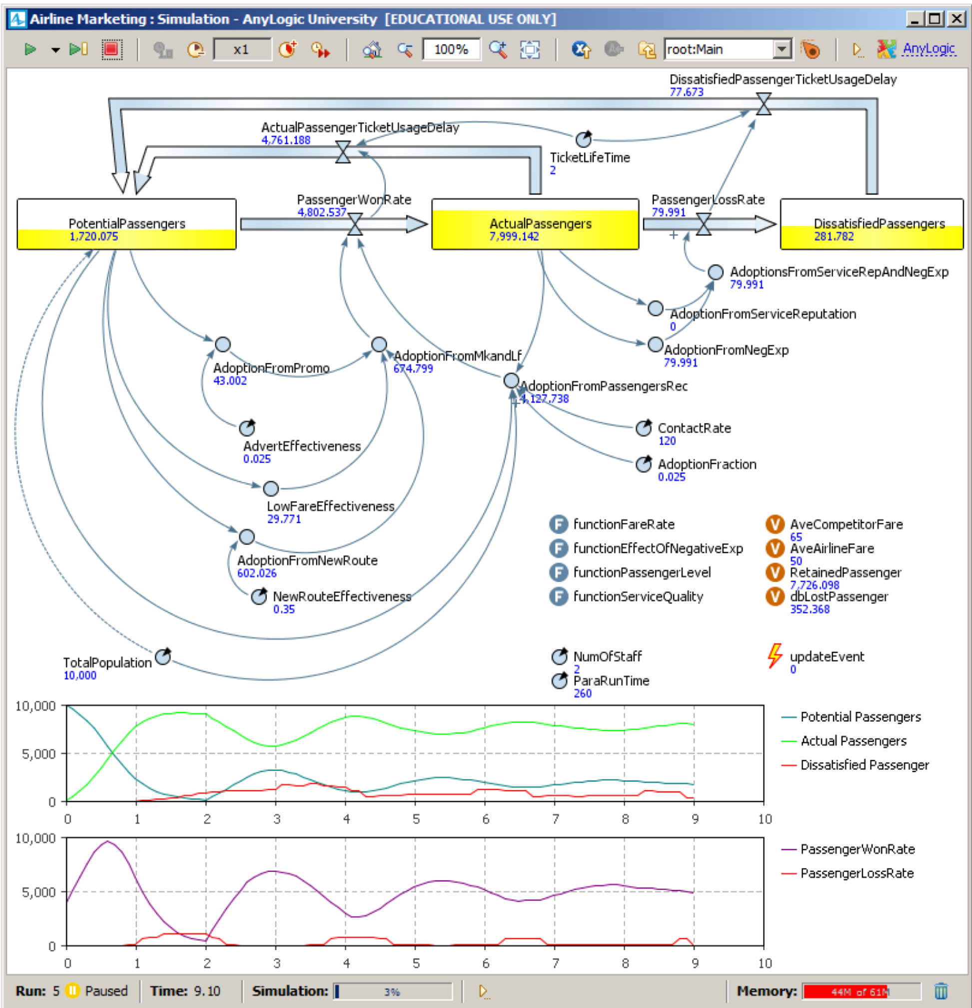


Figure 2: SD simulation execution for hypothetical case study

The flows between stocks can be expressed using the following equations:

PassengerWonRate = AdoptionFromPromo + AdoptionFromPassengersRec

PassengerLossRate = AdoptionFromServiceReputation + AdoptionFromNegExp

PassengerTicketUsage = delay(PassengerWonRate, TicketLifeTime)

LossPassengerTicketUsage = delay(PassengerLossRate, TicketLifeTime)

MODEL VERIFICATION AND VALIDATION

While developing simulation models, it is crucial to gain credibility through verification and validation. This is particularly important for real-world case studies. The model discussed in this paper, however, is purely academic and based on a hypothetical situation due to non-availability of real-world data. It has been thoroughly verified to ensure that the model is programmed correctly, the algorithms have been implemented properly, and the model does not contain errors, oversights, or bugs. Model design and implementation have both been validated by domain experts (face validation). This ensures that the model design is a reasonable representation of the real-world system and that the model implementation produces reasonable outputs. Having done this kind of validation also allows us to draw some conclusions about the potential value of such models for real-world cases.

MODEL EXPERIMENTATION

When we run the simulation for a while we can see some patterns occurring in the two time series windows at the bottom of Figure 2 which are displaying stock level changes over time and the rate changes over time. All outputs in these windows show some oscillating behaviour in the beginning which gets weaker over time and stabilises when the simulation is run for long periods. The fluctuations are caused by the delays embedded in the system. In the following experiments we waited until outputs were stabilising.

For the experimentation we have created four scenarios (see Table 1 for the scenario setup). The goal was to test the usability of the model for decision support. Each of the four scenarios has varying values for the following experimental factors: Number of staff; Ticket Life Time (TLT) [years]; average Competitors' fare (C) [£]; Airline's fare (A) [£]. The total population is 10,000. Our base scenario is Scenario 1 with three service counters open. The investigation could help us to decide if we should rent an additional counter from our competitors or if we could rent out one of our counters to our competitors. In addition, we are able to investigate the payback of some of our marketing efforts. Scenario 1 and 2 both focus on testing the impact of ticket life time on airline performance. Scenario 3 and Scenario 4 both focus on testing the effects of competitive fare advantages on airline performance. The results of the experimentation are represented in Table 2.

Table 1: Experimental setup for the different scenarios

Scenario	No of staff	Ticket Life Time	Fares C	Fares A
		years	£	£
1	2, 3, 4	1	65	50
2	2, 3, 4	2	65	50
3	2, 3, 4	1	50	65
4	2, 3, 4	2	50	65

DISCUSSION

There are some general observations that can be made from the diagrams in Table 2. Providing four service counters (i.e. having four staff present) does not have a practical significant impact on stock or rate changes in the long run compared to the base case of three service counters. On the other hand, opening only two service counters seems to create a space/staff shortage and has a practical significant impact on all stocks and flows in the long run (less potential passengers become passengers, etc.) which is even stronger when ticket life time goes up. Scenarios with space shortage (i.e. only two service counters open) are the only ones where the airline loses passengers in the long run. This is even stronger when ticket life time goes up. We have not invested a huge amount of time in trying to find explanation for all the observed phenomena as we are not solving a real-world case and therefore the explanations are secondary. If this was a real-world case, we would get together with the domain experts and other stake holders to find the causes behind the observed phenomena within the system structure, using the CLD and SD simulation model for discussions.

In the long run, the results suggest that an optimum profit can be made by having three service counters and applying the two year ticket life time policy. The fares do not seem to have a big impact – perhaps the differences between the prices were not radical enough to attract passengers from competing airlines. A sensitivity analysis for this factor would be useful in order to see at what point fares start having an impact.

For this hypothetical case study we are taking a very crude approach to the analysis of the results by just looking at the steady state outcome of the experiments. In a real-world case where the main goal of the experiments would be to influence system behaviour and optimise system performance, we would also have to look at the dynamics of the system over time for each individual scenario and sub scenario (i.e. different number of staff) and not only at the outputs in steady state. Once we have identified a pattern of behaviour that is a problem, we can look for the system structure that is known to cause this pattern. By finding and modifying this system structure we have the possibility to permanently eliminate the problem pattern of behaviour. Another point is that we get the wrong impression if we only look at the steady state; for example, in the diagrams in Table 2 it looks like we have nearly no lost passengers, while in reality (if we look at the diagrams in Figure 2) we have quite a lot of lost passengers over time due to the oscillating behaviour of the model. This kind of information is not contained in the diagrams in Table 2.

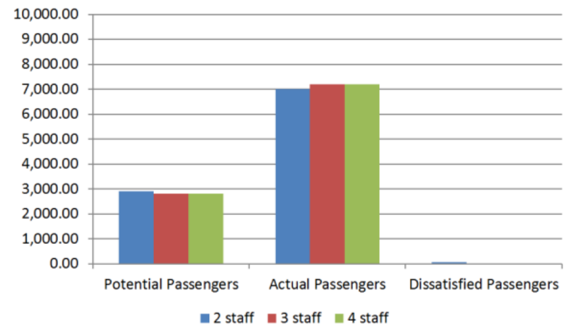
CONCLUSION

Previously we put together an airport model classification with the goal to identify gaps, where simulation modelling would have potential to aid decision making, but is not yet commonly used. One of the gaps we identified was in the area of "airline marketing strategy modelling". As such models would be used for strategic decision making it seemed appropriate to use a SD approach. SD is a powerful methodology and computer simulation modeling technique for framing, understanding, and discussing complex issues and problems and is commonly applied at the strategic level of decision making.

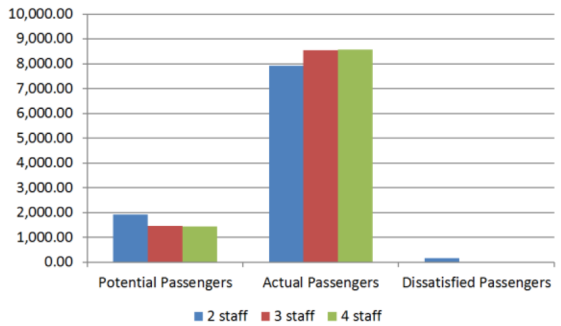
In this paper we have presented a hypothetical case study that employed SD to optimise the marketing strategy of a hypothetical airline. We presented a CLD of the system under study as well as the corresponding SFD. The SFD was then implemented and we run some simulation experiments to test our hypothesis that such SD simulation models and their outputs could benefit decision makers that deal with optimising airline marketing strategies. We found that our diagrams as well as the simulation results revealed some (non-trivial) insights related to the effect of the different marketing strategies we tested.

After showing the potential of SD for developing airline marketing strategies, we are now looking for an airline company that provides us with access to data and expert knowledge, so that we can validate our model through a real-world case study. Once the model has been validated it could be used as a template for other case studies. Another area of development with high potential is the integration of monetary measures. Here we have to consider the costs/benefits in monetary terms for implementing certain marketing strategies, which plays a major role for optimising revenue and profits the organisation makes over time.

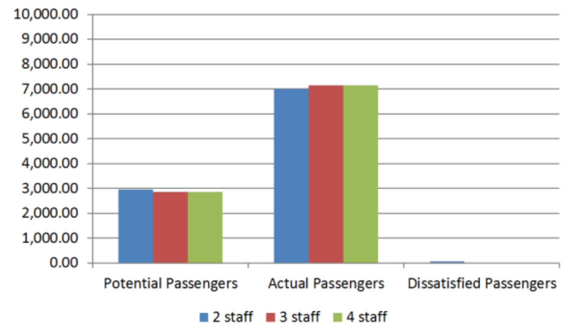
Table 2: Results from the experiments



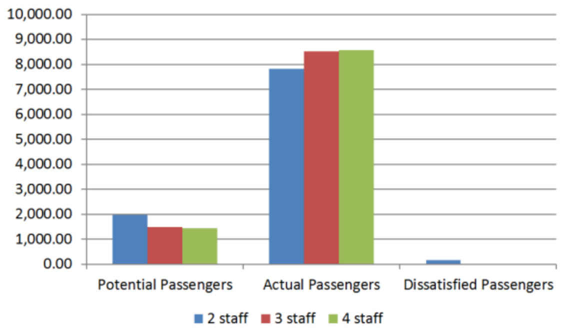
Scenario 1: TLT=1; C>A



Scenario 2: TLT=2; C>A



Scenario 3: TLT=1; C<A



Scenario 4: TLT=2; C<A

We conclude that we have achieved our objective by finding a new opportunity for simulation modelling within the field of airport/airline operation management. We have demonstrated the feasibility of using SD simulation modelling for "airline marketing strategy modelling" and are looking forward to try it out in the real world.

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